A PRIOR PERTINENCE EVALUATION USING FUZZY SET AND BAYES THEORY FOR ESOPHAGUS WALL SEGMENTATION

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Abstract- **In this work, our interest is related to the esophagus inner and outer wall segmentation from ultrasound images sequences. We aim to elaborate a general methodology of data mining that coherently links works on data selection and fusion architectures, in order to extract useful information from raw data. In the presented method, based on fuzzy logic, some fuzzy propositions are defined using physicians *a prior* knowledge. The use of probability distributions, estimated thanks to a learning base, allows the veracity of these propositions to be qualified. This promising idea enables information to be managed through the consideration of both information imprecision and uncertainty. By considering that, the fuzzyfication process is optimized relatively to a given criteria using a genetic algorithm. We conclude this paper with some preliminary results and outline some further works.**

Keywords **– Segmentation, ultrasound, data-mining, fuzzy propositions, veracity, probability, genetic algorithms**

I. INTRODUCTION

In medical imaging and precisely in ultrasound image processing, segmentation studies are often based on the use of *a prior* knowledge given by the physicians experience. As consequence, knowledge based systems appear to be promising approaches for segmentation. By this way researchers aim to imitate human ability for segmentation and thus, hope to increase segmentation robustness. At the present day, we can first consider that the most knowledge based works do not describe clearly how *a prior* knowledge are defined and how to evaluate their gain objectively when they are involved in a decision system. In this work, we introduce a method, which is able to quantify the gain that knowledge can contribute to performance of a segmentation system. After a description of the medical application of this work presented in section 2, the problematic of this study is described. Then, the main considered principles are exposed in section 3. The architecture for evaluating *a prior* knowledge will follow. Some preliminary results are then presented in section 4. Finally, conclusions and perspectives close this paper.

II. MEDICAL PROBLEMATIC

As previously mentioned, the goal of this study is to achieve the detection of esophagus outer wall using sequences acquired with the echoendoscopic imaging system Olympus EU-M3. The catheter, topped with an ultrasound transducer, is introduced into the patient mouth and progress along the esophagus lumen, toward the cardia. Ultrasound waves are emitted in the progression transversal plane and, thanks to reflections, an image reconstruction is possible. The catheter progression is mechanically controlled using a developed acquisition system, so images can be captured with a constant spacing in order to ensure 3D reconstruction capability.

In Fig. 2, the difficulties represented by this kind of images can be appreciated. Their quality depends mainly on two phenomena: the speckle noise (due to the ultrasound imaging approach) and multiple waves reflections [1][2], called "harmonics" due to the transducer outer-sheath. The esophagus fine structure can be analyzed with this diagnosis procedure that explains the efficiency of endosonography in medical "staging" of esophagus tumors.

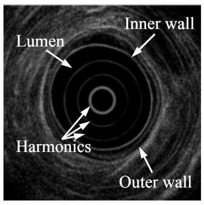

Fig. 2. An endosonographic image. Notice the esophagus fine structure scheme: esophagus wall is composed of several layers alternatively hyper (brilliant) and hypo-echoic (dark).

The general developed methodology is based on the fusion of methods, where the complementary aspects of different approaches are exploited in order to obtain best results. In our particular case, esophagus wall segmentation is achieved by combining a fuzzy model, which enables the integration of physicians knowledge on echographic imaging (echogenecity, echostructure, harmonics positions), and a dynamic model to take into account *a prior* knowledge on the researched anatomical structures (shape, contour regularity). In this paper, we focus on the fuzzy process. Our goal is to develop an approach of data-mining, which consist on the evaluation of *a prior* pertinence using a learning base (LB).

III. METHODOLOGY

The methods of supervised classification aims to relate the observation space (or feature space) to the decision space. In medical imaging several imperfections can affected the considered LB: if the observations are ambiguous, then the consideration of fuzzy propositions P_i is needed, whereas if the imperfections concerns the class C_i, we have to consider fuzzy set in the decision space (Fig. 3).

In our particular case, we try to evaluate the power of the relation between fuzzy sets (associated to fuzzy propositions) defined in the observation space, and the possible decisions defined in the decision space.

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Abstract

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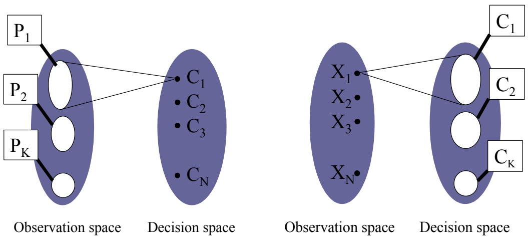

Fig. 3. Learning base possible imperfection

Also the learning base is constructed as follows:

$$B=\{(\{P_k\},W_i), i\in\{1,...,n\}\} \qquad (1)$$

where $\{P_k\}$ is a set of fuzzy propositions corresponding to *a prior*, and μ_{Pk} the membership function associated. By this way, we can envisage to define fuzzy sets associated to some fuzzy propositions, which maximize the probability to classify a pixel in the right class. In the same time, the attribution of a veracity degree becomes possible and can be considered during an eventual fusion process of each considered fuzzy concepts.

A. Fuzzy image concept

Let's introduce first, the concept of fuzzy images based on the theory of Zadeh [3]. A fuzzy image is defined as the transformation of an image (considered as a *MxN* array of gray level associated with each pixel) into an image with the same dimensions, where each pixel is associated with a value denoting the reliability of possessing a fuzzy property *P*:

$$\begin{aligned} A: M \times N &\rightarrow [0;1] \\ I(i,j) &\rightarrow \mu_P(I) \end{aligned} \qquad (2)$$

where, $\mu_P(I)$ reflects the appropriateness or the validity of the fact that the pixel $I(i,j)$ possesses the fuzzy property "*P*". Concerning the application of the esophagus wall detection, four fuzzy images are defined. Similarly to [1][4], the following concepts are represented in terms of fuzzy images:

Harmonics: Before starting any echoendoscopic processing method, the characteristics of the harmonics (i.e. their positions as well as their gray level distributions) must be known, else they will impinge on the extraction of useful information.

Region: Due to the acquisition system, a strong contrast defines two different regions, which can be easily distinguished: esophagus lumen (appears in black) and tissue area (appears usually brilliant). This information is very precious for the computation of inner wall belief image.

Contour: The concept of a contour is strong information on the presence of the esophagus inner and outer wall. A gradient operator, defined by two 5x5 convolution masks, similar to Sobel operator, is used to estimate contours in the data volume.

Intensity: Given the fact that a hyper-echoic tissue (for example the inner and outer wall) appears as brilliant in an ultrasound image, the gray level intensity is an important feature to consider.

B. Probability of a fuzzy event

In this work, in order to characterize esophagus wall, we focus our interest on the two following fuzzy propositions:

- "Esophagus wall is brilliant" - P_1
- "Esophagus wall is a contour" - P_2

These propositions are defined by using physician *a prior* knowledge: inner wall and outer are hyperechoic (that means they have a high ability to reflect ultrasound), inner wall is located between esophagus lumen and mucous that are hypoechoic, whereas outer wall is situated between muscular membrane and internal tissues, that are hypoechoic in comparison.

Our approach lies on the closed world assumption where the possible events are grouped in the set $\Omega=\{W_1, W_2,..., W_N\}$. The possible events correspond in our particular case, to inner wall (object 1), outer wall (object 2) and others tissues (object 3). In this context, we assume that it is possible to do the hypothesis of exclusivity and exhaustivity. Thus, That means in this study we have:

$$\sum_{i=1}^{N} p(W_i)=1 \text{ and } \forall i \neq j, W_i \cap W_j = \{\phi\} \qquad (3)$$

From this starting point, we can commonly consider the problem according to the Bayes model. Given the a stochastic vector of features labeled $X(i,j)$, which attributes at each pixel (i,j) a set of features, we can express the following conditional probabilities:

$$p(W_i/X(i,j)=x)=\frac{p(X(i,j)=x/W_i)\cdot p(W_i)}{p(X(i,j)=x)} \qquad (4)$$

If we assume now that the vector of features is not an event perfectly accurate that means that the object is defined by a fuzzy proposition as for example "being brilliant" or "being tall", then it is possible to talk in terms of probability of fuzzy events because a probability is associated to an ambiguous concept. Such fuzzy proposition can be associated to a membership function taking its values in $[0;1]$. By using the Bayes expression, we can express the *a posteriori* probability to observe the class W_i given the membership value to a given concept given by the fuzzy proposition *P*.

$$p_1 \left\{ p(W_i/\mu(i;j)=\mu)=\frac{\overbrace{p(\mu(i,j)=\mu/W_i)}^{p_2}\cdot p(W_i)}{p(\mu(i,j)=\mu)} \right. \qquad (5)$$

• $p(W_i)$ is the probability of each class W_i. This probability is directly estimated for each class from the predefined learning base.

• $p(\mu_P(i,j)=\mu)$ represents the probability distribution to observe a given membership value on the LB. This

probability distribution is directly estimated from the LB histogram of membership values.

• $p(\mu_P(i,j)=\mu \mid W_i)$ -or p_2- corresponds to the probability to observe a given membership value, corresponding to a given concept, knowing the class W_i. This means that the distribution of probabilities can be estimated by the exploitation of the membership value histogram on the class W_i. This estimation is achieved by using the LB defined before.

• $p(W_i|\mu_P(i,j)=\mu)$ -or p_1- corresponds to the probability to classify a given pixel in the class W_i, knowing its membership value to the concept P. In other terms, this probability gives the appropriateness of the considered fuzzy set defined by μ_P to characterize the class W_i.

Considering the learning base, it is possible to evaluate how a particular fuzzy proposition characterizes each class. We have to answer the two following questions: which membership function has the best power to characterize a class, and in the same time, how can we define the fuzzy proposition veracity, relatively to this class?

C. Veracity of a fuzzy proposition

Given the fuzzy proposition P (based on a fuzzy concept) and an the associated membership function μ_P, then an example of belief probability distributions can appear as in Fig. 4.

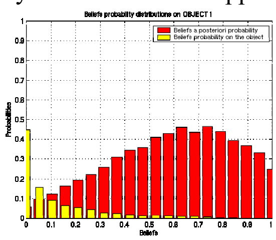

Fig. 4. An example of beliefs probabilities distribution

In Fig. 4, we can notice that high membership values are preponderant on *a posteriori* probability distribution. This means that, given a membership value, the probability to observe the considered class is significant. On the other hand, from the examination of beliefs *a prior* distribution on the learning object, we can notice that the probability to observe high beliefs is low. In this case, the chosen membership function is not sufficient. Then, a criterion to be satisfied by the membership function can be defined using the following considerations:

• The distribution p_2 have to contain "significant" probability. This means that the maximum (MAP) of the *a posteriori* probability $p_m=p(W_i|\mu_P(i,j)=\mu)$ must be considered in the criterion.

• The significant probabilities have also to correspond to any "important" membership values. Thus, we must include the corresponding membership value in the final criteria which is defined as follows:

$$\mu_m=\mathrm{argmax}\left[p\left(W_i/\mu_P(i,j)=\mu\right)\right] \qquad (6)$$

• On each object, high membership values have to be in majority in the beliefs distribution. This means that this distribution of probability must be skewed toward the high membership values. In this work, the estimation of the distribution skewness κ is given by (9),

$$\kappa=\frac{\overline{\mu}-\widetilde{\mu}}{\sigma_\mu} \qquad (7)$$

where $\overline{\mu}$, $\widetilde{\mu}$ and σ_μ denote the mean, the median and the standard deviation of the $\mu(i,j)$ distribution.

• Finally, the distribution p_1 must be the more uniformly distributed as possible, to preserve sufficient information during all the process. As consequences, the consideration of the entropy S will ensure that data will not be reduced to only one value. Its expression is as follows:

$$S=-\sum_i p_i\cdot\log(p_i) \qquad (8)$$

By considering these constraints, we can define a final criterion, which can be also considered as a veracity measurement of the fuzzy proposition P. The searched membership function must maximize this criterion, which is defined in general as follows:

$$\Gamma(p_m,\mu_m,p_2)=f(p_m)\cdot g(\mu_m)\cdot h(\kappa(p_2))\cdot i(S(p_2)) \qquad (9)$$

In the last expression, f is an increasing function of the p_m, g is an increasing function of the membership value μ_m associated with p_m, h and i are respectively increasing functions of the beliefs distribution skewness and entropy. The considered functions take all their values in the interval *[0;1]*. To conclude, the searched membership function is defined by the following expression:

$$\mu_{P_{opt}}=Arg\max\left[\Gamma(p_m,\mu_m,p_2)\right] \qquad (10)$$

D. Genetic processing

We propose here a genetic algorithm [5] in order to find optimal membership functions corresponding to fuzzy propositions. In the particular case of this study, we parameterize the membership function by a S-Shape function $S_{a,b,c}$, which depends on three parameters a, b, and c.

A family of random solutions $\{G_i\}$ (the chromosomes) is initially computed in the search space Δ, which is a bounded by the maximum value authorized for the given scalar feature in the entire learning base. First solutions elaboration step being ended, three kinds of operators are now applied on each chromosome. During the reproduction stage, best chromosomes are duplicated, in order to build a new set. The likelihood of duplication depends on values of the fitness function, which are computed on each chromosome. Several crossovers, which correspond to chromosomes melting, are operated on $\{G_i\}$. The main advantage of this kind of operator is to speed up the algorithm convergence. The mutations operated on $\{G_i\}$ ensure that all the search space is taken into

account. Therefore, chances that the coefficients being stabilized in a local minimum are reduced. Mutations are accomplished with an uniform likelihood law. At each generation, the best solution, corresponding to the best set of fuzzy function parameters relative to (10), is retained from the original solutions set. The genetic progress is stopped when the standard deviation of the fitness function on each chromosome is less than a threshold, which is a percentage of the mean fitness value computed in the chromosome set/family. In the case where this condition is not realized, the genetic process is stopped after a given number of iterations N_{gen}. Finally, we compute the parameters histogram, in order to choose the best solution.

III. Prelimanary Results

This section presents first experiments obtained from real sequences acquired in the Brest center hospital (France). The set of possible events is composed of three elements $\Omega=\{W_1,W_2,W_3\}$ where W_1="inner wall" – W_2 = "outer wall" and W3="other tissues". The constituted learning base is composed, for instance, of two hundred images of non-pathologic cases. Two fuzzy propositions are here considered: P_1="local gradient is high" and P_2="gray level is high".

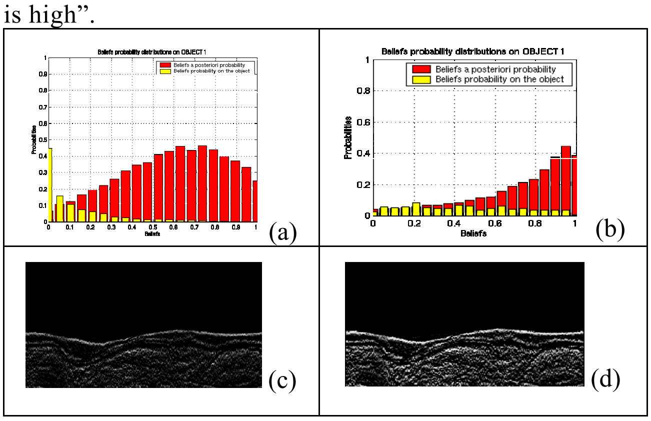

Fig. 5. Study of the fuzzy proposition P_1 on the esophagus inner wall. (a) and (c) corresponds a non-optimal membership function whereas (b) and (d) corresponds to an "optimal" membership function.

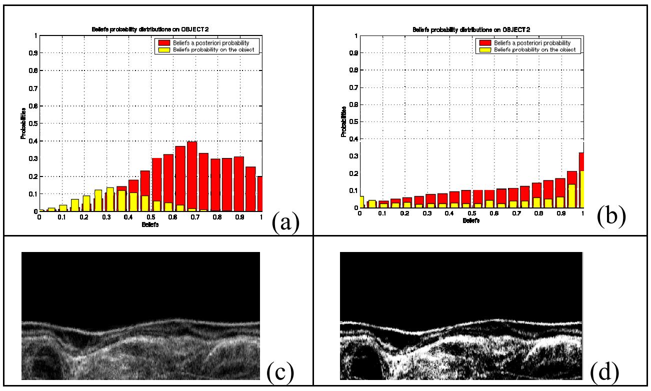

Fig. 6. Study of the fuzzy proposition P_2 on the esophagus outer wall. (a) and (c) correspond a non-optimal membership function whereas (b) and (d) correspond to an "optimal" membership function.

The Fig. 5 and Fig. 6 presents obtained histograms for the cases of esophagus inner and outer walls. We can appreciate how it is possible to increase the reliability of *a prior* through the optimization of membership functions using a learning base. The Fig. 5.a, 5.c and Fig. 6.a, 6.c present the obtained histograms with non-optimal membership function, whereas Fig. 5.b, 5.d and Fig. 6.a, 6.b correspond to optimized membership function.

TABLE I: Veracity of fuzzy proposition for inner and outer wall

	Measurements	μ_{P1}	$\mu_{P1\ opt}$	μ_{P2}	$\mu_{P2\ opt}$
Inner wall	P_m	0.46	0.78	0.2	0.1
	μ_m	0.6	0.9	1	0.8
	κ	-1.9	-0.3	-2.5	-0.1
	S	2.5	2.80	2	2.5
	Veracity	0.01	0.28	0.003	0.004
Outer wall	P_m	0.3	0.27	0.3	0.38
	μ_m	0.8	1	0.6	1
	κ	-2.5	-1.1	0.4	-0.5
	S	2	2.2	2.3	2.7
	Veracityl	0.007	0.025	0.03	0.25

As we can see in Table 1, the "brilliancy proposition" cannot well discriminate between esophagus inner wall to the other anatomical structures due to a veracity of 0.004. In comparison with the "contour proposition" is more pertinent with a veracity of 0.28. Otherwise, the ability the "contour proposition" has to separate outer wall from other anatomical structures appears significant with a veracity equal to 0.25, in comparison with "brilliancy proposition", which just has in the "optimal case" a veracity of 0.025.

IV. Conclusions

Some preliminary results, obtained with this approach, give elements to envisaged the possibility to quantify a particular aspect of the fuzzy propositions veracity, in considering another aspect of the information imperfection: the probabilistic uncertainty. Results have shown, for some simple examples of fuzzy propositions, that a blink use of *a priori* knowledge given by physicians is not always sure.

In this work, *a priori* knowledge has been evaluated before any fusion process. The next step of this study will be to optimize fuzzy function after the *a priori* knowledge has been combined in a fusion process. By this manner, it will be possible to consider the step of data-mining and the fusion process as a coherent whole.

V. References

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